Wealth Inequality and Intergenerational Income Mobility in the United States

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Abstract

Where income inequality is higher, intergenerational mobility in income is lower. Income inequality affects upward mobility because exposure to socioeconomic disparities during childhood influences economic opportunities. Beyond income, wealth is also distributed unequally and can facilitate the hoarding of opportunities. Therefore, this study investigates whether wealth inequality is negatively associated with intergenerational income mobility. To examine the impact of childhood exposure to wealth inequality on upward mobility in income, this study utilizes a unique, novel database that makes local estimates of wealth inequality across the United States publicly available. Results from linear models estimated by OLS reveal a clear, negative association between childhood exposure to wealth inequality at the commuting zone level and mobility outcomes later in life. This relationship persists when accounting for levels of income, wealth, and income inequality, as well as other economic and demographic characteristics. Static counterfactual simulations suggest that childhood exposure to wealth inequality has more significant consequences for upward income mobility than income inequality itself.

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1. Introduction

Where income inequality is higher, intergenerational mobility in income is lower. This observation, commonly referred to as 'The Great Gatsby Curve', stands in striking contrast to the American Dream of upward mobility (Corak 2013). The negative association between income inequality and intergenerational mobility has been documented both within and between countries (Chetty et al. 2017; Chetty and Hendren 2018b; Chetty et al. 2014a; Corak 2013; DiPrete 2020).

Income inequality matters for upward mobility because childhood exposure to socioeconomic inequality influences economic opportunities (Corak 2013). In other words: where children grow up has a permanent imprint on how they fare later in life (Chetty and Hendren 2018a; Chetty and Hendren 2018b; Chetty, Hendren, and Katz 2016; Chetty et al. 2014b). For a recent birth cohort in the United States, a one standard deviation increase in commuting zone-level income inequality during early adulthood is associated with a 0.63 standard deviation reduction in upward mobility (Chetty et al. 2014a).

Beyond income, wealth is also distributed unequally. The concentration of wealth can monopolize opportunities, drive up the cost of living in better neighborhoods, or constrain financial risk-taking and business opportunities for some while enabling them for others. In short, opportunity hoarding (Tilly 2000) goes beyond income.

Is childhood exposure to wealth inequality negatively associated with upward income mobility? While previous research has convincingly documented how income inequality depresses intergenerational income mobility, a lack of wealth data has meant that no such evidence is available for the link between wealth inequality and upward mobility in income.

To investigate the role of childhood exposure to wealth inequality for intergenerational income mobility, this study draws on a unique and novel database that makes estimates of wealth inequality in commuting zones across the United States publicly available (Suss, Kemeny, and Connor 2024). This dataset is combined with estimates of intergenerational income mobility provided by Opportunity Insights (Chetty et al. 2020a) and commuting zone characteristics from the Decennial Census.

Results from linear models estimated by OLS show a clear, negative association between CZ-level wealth inequality in early adolescence and upward income mobility outcomes later in life. This relationship persists when accounting for levels of income and wealth as well as income inequality and other economic and demographic characteristics. Static counterfactual simulations suggest that childhood exposure to wealth inequality is more consequential for upward mobility in income than income inequality itself.

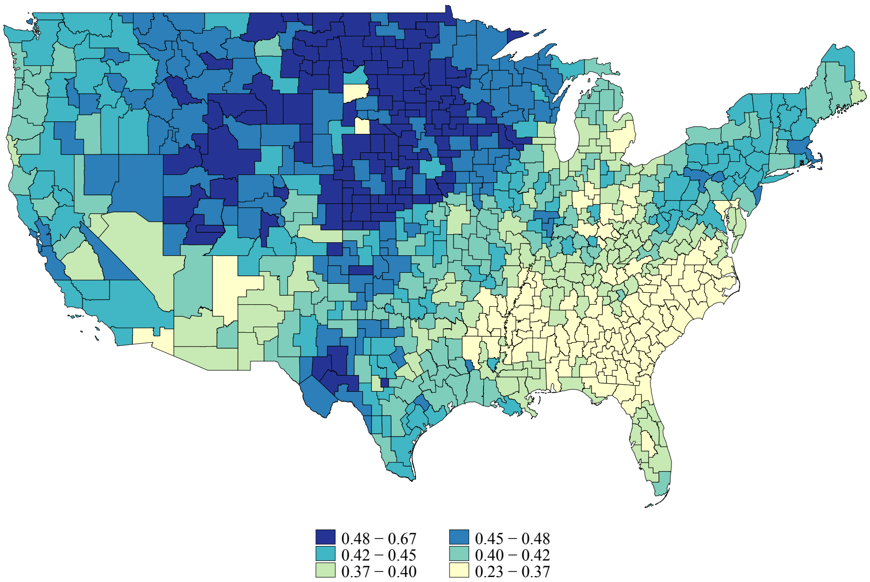
2. Results

2.1. The distribution of opportunity and wealth inequality

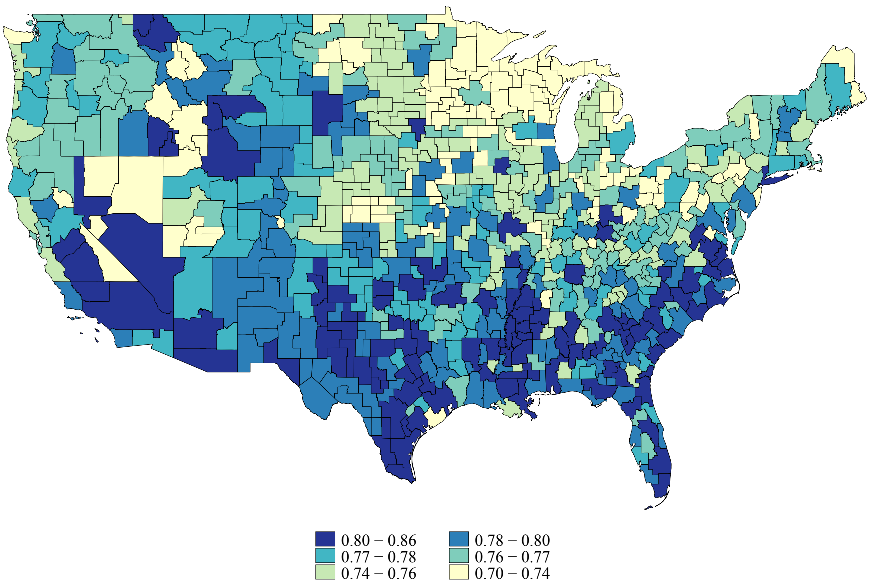
Can the spatial distribution of intergenerational income mobility and wealth inequality give us any indication of whether the two are correlated? Figure 1a plots the geographical distribution of upward income mobility and figure 1b shows the Gini index of wealth inequality across commuting zones. These maps indicate substantial spatial clustering: Upward income mobility is lowest in the South—particularly so across CZs in the cotton belt—and highest in the Midwest. Conversely, wealth inequality is higher in the South and lower in states like Minnesota or Wisconsin. However, some CZs combine relatively high upward income mobility with high inequality in wealth (for instance, New York), or vice versa. Overall, these maps reveal substantial variation in both intergenerational income mobility and wealth inequality across the United States.

Figures 2a and 2b assess the relationship between intergenerational mobility in income and wealth inequality more directly. Panel A shows the bivariate association between upward income mobility and the Gini index of wealth; Panel B plots the same mobility measure against the share of wealth held by the top 10%. In places where wealth was distributed more unequally, intergenerational income mobility of low-income children is lower. More specifically, on average, children growing up in families at the 25th percentile of the national income distribution in commuting zones with relatively low inequality in wealth (Gini index 0.70) climb up to the 47^{th} percentile in adulthood. However, their peers in commuting zones that exhibit relatively high inequality in wealth (Gini index 0.85) only achieve incomes around the 37^{th} percentile of the national income distribution. The pattern is similar when using the share of wealth held by the top 10% instead of the Gini index.

Figure 1: Geographic variation in upward income mobility (Panel a) and wealth inequality (Panel b) across commuting zones



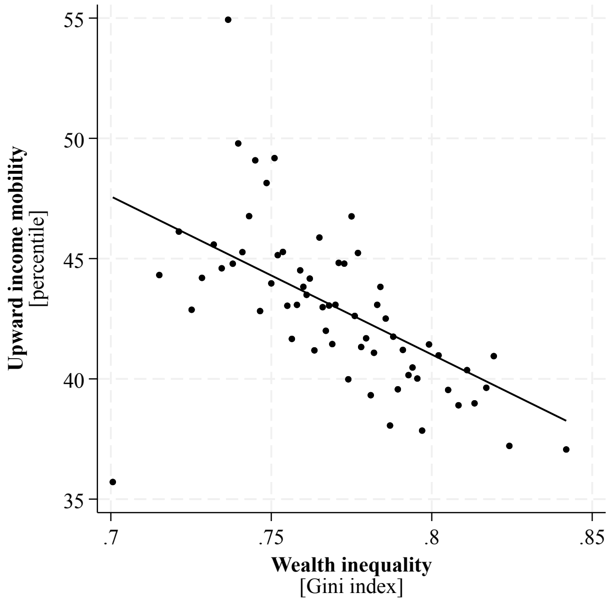
(a) Upward income mobility



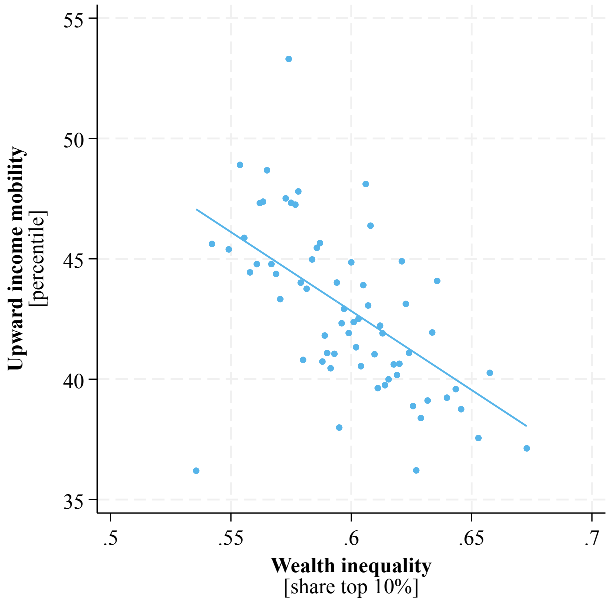
(b) Wealth inequality

Note: Upward income mobility in Panel (a) is measured as the estimated average percentile rank in the national income distribution that children growing up to parents at the 25^{th} income percentile achieve in adulthood. Estimates are based on data published by Opportunity Insights. Wealth inequality in Panel (b) is measured as the commuting zone level Gini coefficient. Estimates are from the GEOWEALTH-US project.

Figure 2: Binned bivariate association between wealth inequality and upward income mobility across commuting zones



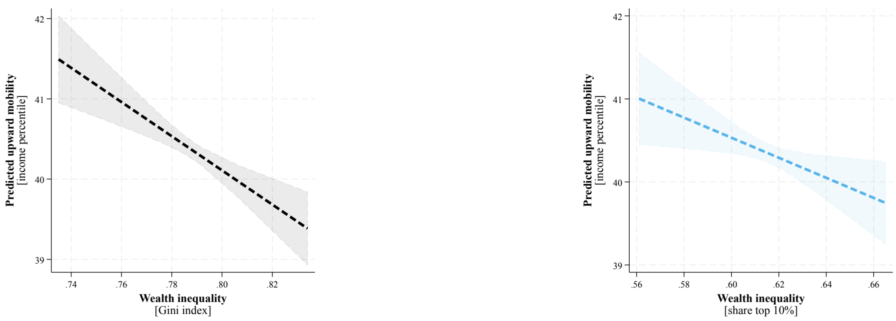
(a) Gini index



(b) Top 10% wealth share

Note: All commuting zones are grouped into 70 equal-sized bins. In both panels, upward income mobility is measured as the estimated average percentile rank in the national income distribution that children growing up to parents at the 25^{th} income percentile achieve in adulthood. Estimates are based on data published by Opportunity Insights. Wealth inequality is measured as the commuting zone level Gini coefficient in Panel (a) and the share of wealth held by the top 10% in panel (b). Estimates based on the GEOWEALTH-US project.

Figure 3: The association between wealth inequality and upward income mobility as predicted by multivariate linear models



(a) Gini index (b) Top 10% wealth share

Note: Figure displayes the linear prediction with 95% confidence intervals. In both panels, upward income mobility is measured as the predicted average percentile rank in the national income distribution that children growing up to parents at the 25^{th} percentile achieve in adulthood. Mobility data is based on information published by Opportunity Insights. Wealth inequality is measured as the commuting zone level Gini coefficient in panel A and the share of wealth held by the top 10% in the panel B. Wealth data are from the GEOWEALTH-US project. Author's calculation.

2.2. Linear models: wealth inequality and upward income mobility

Are areas with higher inequality in wealth less upwardly mobile in income? Figures 2a and 2b suggest a direct, negative relationship between CZ-level wealth inequality in early adolescence and the incomes achieved by low-income children later in life. However, the bivariate association cannot account for other characteristics of commuting zones that might explain spatial differences in upward economic mobility.

Figures 3a and 3b plot predicted upward income mobility and wealth inequality from linear models estimated by OLS. Panel A shows the predicted association for the Gini index, and Panel B for the top 10% wealth share. Both models adjust for CZ-level median wealth, mean income, income inequality, population, income growth, share of Black population, racial segregation, share of the population with a college degree, mean age, immigration, and the share working in manufacturing, as well as characteristics of the children in the Opportunity Insights data, namely the share married, the fraction who stayed in the commuting zone they grew up in, and the proportion with a father present during early adolescence. Full model results are shown in Appendix Table A2.

Accounting for CZ characteristics, in areas where wealth was distributed more unequally, the upward income mobility outcomes for low-income children are lower. In other words: children growing up in families at the 25^{th} percentile of the national income distribution are less upwardly mobile in areas where wealth inequality is higher. Children growing up in commuting zones at the 10th percentile of the spatial distribution of wealth inequality (Gini index 0.735) are estimated to climb up to the 41.5^{th} percentile of the national income distribution in adulthood; whereas their peers in commuting zones at the 90^{th} percentile of the spatial distribution of wealth inequality (Gini index 0.835) only climb up to the 39.5^{th} percentile of the national income distribution. This association holds net of income inequality and the other economic and demographic characteristics mentioned above.

2.3. Counterfactual inequality simulation

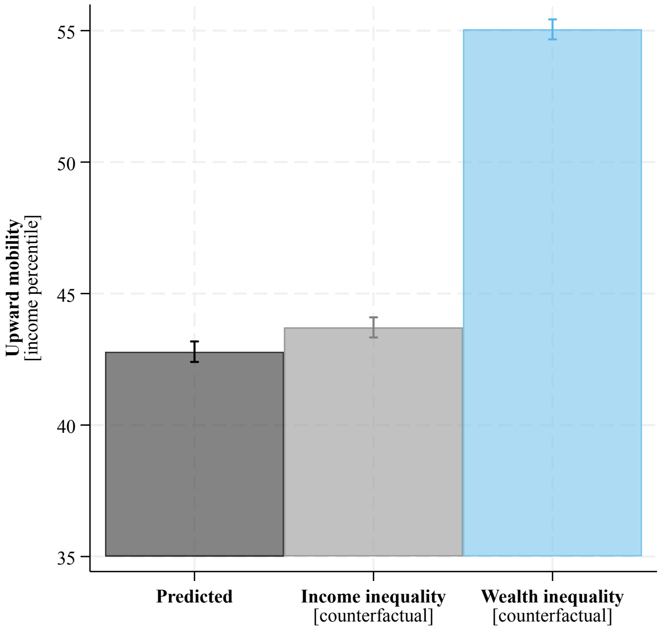
What would intergenerational income mobility look like if these children were exposed to less income or wealth inequality during childhood? The linear model can be used for a simple exercise: Let's suppose either wealth inequality or income inequality were reduced by 50 percent. Figure 4 plots the predicted average upward income mobility of low-income children for the observed and the two counterfactual scenarios.

In the baseline model, the average predicted income achieved in adulthood is around the 42^{nd} percentile of the national income distribution. This figure is only marginally increased in the counterfactual scenario where CZ income inequality is reduced by 50 percent during children's early adolescence. Predicted upward income mobility jumps to the 55^{th} percentile in the counterfactual scenario where wealth inequality (measured with the Gini index) is shrank by 50 percent. Put differently, a 10 percent decrease in commuting zone wealth inequality is estimated to be associated with roughly a 2.5 percentile rank increase in the upward income mobility of low-income children.

2.4. Potential pathways

One way through which inequality might shape disparities in economic opportunities is through its effect on education. Previous research has shown how income inequality is negatively associated with both access to and financial returns to education (Jerrim and Macmillan 2015). Wealth inequality might similarly lead to disparities in access to college education with downstream consequences for upward economic mobility (see, for exam-

Figure 4: Static counterfactual simulations of upward mobility in income



Note: Figure shows predicted upward income mobility for actual and counterfactual scenarios. Counterfactual scenarios are modelled as a 50% decline in income inequality (center) and wealth inequality (right), everything else equal. Whiskers indicate 95% confidence intervals. In both panels, upward income mobility is measured as the predicted average percentile rank in the national income distribution that children growing up to parents at the 25^{th} percentile achieve in adulthood. Data are based on information published by Opportunity Insights. Income inequality and wealth inequality are measured as the commuting zone level Gini coefficient. Data are from the GEOWEALTH-US project. Author's calculation.

ple, Hällsten and Pfeffer (2017) and Pfeffer and Killewald (2018)). Appendix Table A3 demonstrates that childhood exposure to higher wealth inequality is indeed negatively associated with the likelihood that low-income children in the Opportunity Insights data attend some college, thereby underscoring a potential pathway through which wealth inequality can shape intergenerational upward mobility in income.

A second pathway through which childhood exposure to inequality might impact income mobility outcomes is through household formation. That is, recent research demonstrates the centrality of educational assortative mating for explaining household-level income inequality (Eika, Mogstad, and Zafar 2019) and shows that partners sort according to wealth over and above sorting by income (Lersch and Schunck 2023). Appendix Table A5 examines whether low-income children growing up in commuting zones with higher wealth inequality are less likely to be married in their mid-30s. This simple exercise suggests no association between wealth inequality and low-income marriage once the models adjust for income inequality.

2.5. Robustness checks

In supplementary analyses, the main models presented here are replicated substituting the outcome measure of intergenerational income mobility with two different operationalizations of upward mobility: (1) the probability that a child born to parents in the bottom quintile of the national income distribution climbs up to the top quintile in adulthood, and (2) the causal effect of place for children born to families at the 25^{th} percentile. This measure indicates the estimated percentage increase in income from experiencing one additional year of childhood exposure to a given commuting zone. Both measures are provided by Chetty et al. (2014). Appendix Tables A6 and A7 show that exposure to wealth inequality remains negatively associated with both alternative outcome specifications.

Next, upward income mobility in the U.S. is systematically confounded by structural racism. That is, Black Americans are often living in racially segregated and disadvantaged neighborhoods, at the same time they are also less upwardly mobile across all states (Chetty et al. 2020b). The main linear models presented here adjust for racial segregation in early adulthood, yet they might yield biased estimates if commuting zones with more prevalent historical racial regimes (Baker 2022) exhibit both, higher wealth inequality and concentrated Black disadvantage in upward income mobility (and Black children are clustering in low-income families). Appendix Table A8 replicates linear models for White children only, thereby ensuring the negative association of wealth inequality and intergenerational income mobility is not confounded by the level of structural racism.

Commuting zone wealth inequality is measured in 2000. This year best matches the time when children in the Opportunity Insights data are still reported on their parents' income tax returns. It is also the timing closest to early adolescence—a period where neighborhood exposure matters most for future economic mobility prospects (Chetty et al. 2020a). Measuring exposure to wealth inequality at other time periods likely introduces measurement error and a mismatch regarding when exposure to wealth inequality matters for economic opportunities. To further substantiate this justification of exposure timing, Appendix Figure A1 plots the estimated coefficient from seven separate models, each identical to the specification presented in the main analysis yet measuring wealth inequality in 10-year intervals from 1960 to 2020. The estimated coefficient is largest when wealth inequality (Gini index) is measured during early adolescence and not associated with upward mobility when measured before children are born or when they are in their 30s.

Last, results are not sensitive to other model specifications, such as weighting commuting zones by the inverse variance of the underlying mobility estimates (Appendix Table A9) to account for the estimated nature of the dependent variable (see Hornstein and Greene (2012)) nor to winsorizing extreme values (Appendix Table A10). In addition, results remain unchanged when using income mobility estimates at the individual- rather than the household-level (Appendix Table A11), and also when measuring income inequality as the Gini index of the bottom 99% (Appendix Table A12). The negative association also holds when restricting the sample to commuting zones in the South and the non-South, respectively (Appendix Table A13).

3. Discussion

Previous research convincingly demonstrated that intergenerational upward mobility in income is lower where income inequality is higher. This association, infamously coined as the 'Great Gatsby Curve', persists both within and between countries (Chetty and

Hendren 2018b; Corak 2013; Durlauf, Kourtellos, and Tan 2022). Childhood exposure to income inequality has become central to our understanding of equality of economic opportunity. However, just like income, the unequal distribution of wealth can also affect 'dreamhoarding' (Reeves 2017) and unequal access to income-generating opportunities.

This study investigates the association between wealth inequality and upward income mobility. More specifically, this article examines how childhood exposure to inequality in wealth at the CZ-level relates to upward mobility in income of children born to low-income families. The study draws on a unique and novel database that makes estimates of wealth inequality at the commuting zone level publicly available (Suss et al. 2024).

Results from linear models estimated by OLS show a clear, negative association between CZ-level exposure to wealth inequality in early adolescence and upward income mobility outcomes later in life. In other words: low-income children growing up in commuting zones with higher wealth inequality achieve lower incomes in adulthood compared to their peers growing up in commuting zones with lower inequality in wealth. This relationship is robust when accounting for levels of income and wealth as well as income inequality and other economic and demographic covariates. Static counterfactual simulations suggest childhood exposure to wealth inequality is more consequential for upward mobility in income than income inequality itself.

Estimates of intergenerational income mobility at the commuting zone level are only available for a single cohort of children born between 1978 and 1983. Therefore, the ability to make causal claims or test mechanisms is severely constrained. At the same time, ideally, one would examine exposure to inequality in wealth on a more granular level than currently feasible. However, there is broad interest in understanding the (potentially) negative consequences of wealth inequality, particularly so in light of the sky-rocketing wealth concentration in recent decades. This study provides a first glimpse into the data and can serve as a starting point for future investigation.

All told, this article provides novel evidence suggesting a strikingly clear, negative association between childhood exposure to wealth inequality and intergenerational upward mobility in income later in life. The findings underscore the need for policymakers to consider the disparate consequences of wealth inequality on the likelihood that low-income children will achieve the American Dream.

4. Material and methods

4.1. Replication

Data and code necessary to reproduce this study can be accessed via a repository at the Open Science Framework (Insert OSF Link here).

4.2. Data sources

First, this study builds on data published by Opportunity Insights (Chetty et al. 2020a). Opportunity Insights provides mobility estimates from parent-child linked income tax returns from the IRS as well as commuting zone characteristics obtained through the American Community Survey (ACS). Second, this study draws on recent local-area wealth estimates from GEOWEALTH-US (Suss, Kemeny, and Connor 2024). This novel database builds on the Survey of Consumer Finances (SCF) and public-use Decennial and American Community Survey (ACS) microdata from the U.S. Census Bureau and applies machine-learning-based imputation to estimate wealth at several spatial levels. GEOWEALTH-US provides numerous estimates of wealth and wealth inequality between 1960 and 2020 for PUMAs, commuting zones, metro areas, and 48 states.

4.3. Measures of wealth inequality

GEOWEALTH-US constructs average wealth and wealth inequality variables for commuting zones by building a model of household-level wealth drawing on the SCF that is then used to impute wealth using Census population survey data. Next, GEOWEALTH-US uses Pareto tail estimation to account for wealth inequality at the top in the Decennial Census and American Community Survey. Finally, wealth aggregates and wealth inequality indicators are estimated for each commuting zone (Suss, Kemeny, and Connor 2024). This study uses two different measures of wealth inequality provided by GEOWEALTH-US: (1) the Gini index and, (2) the wealth share held by the top 10% of the CZ wealth distribution. Appendix Figure A2 shows the distribution of wealth inequality (Gini index).

4.4. Measure of intergenerational income mobility

Intergenerational income mobility is measured using data from Opportunity Insights who provide estimates of the income mobility outcomes of children born between 1978 and 1983 (Chetty et al. 2020a; Chetty et al. 2014a). The main measure of upward mobility in income is the estimated mean income percentile rank achieved by children raised by families at the 25^{th} percentile of th national income distribution. Parents' income is measured based on income tax returns in the late 1990s, while the mobility outcomes of their children are measured in 2014-2015. Appendix Figure A3 shows the distribution of upward income mobility estimates.

4.5. Linear models

This study estimates the relationship between wealth inequality and upward income mobility across commuting zones using linear models estimated using ordinary least squares regression:

$$Y_c = \alpha_1 G_c + \beta_1 X_c + \varepsilon_c \tag{1}$$

Where Y_c is the commuting zone-specific income mobility outcome of children born to low-income families, G_c indicates commuting zone-level Gini index of wealth inequality (or the top 10% wealth share, respectively), and X_c denotes a vector of commuting zone covariates detailed below. All main models are estimates using bootstrapped standard errors.

Covariates are included stepwise: The first model gives the simple, bivariate association without any CZ-level covariates. The second model adds mean income (log), median wealth (log), income inequality (Gini index), population (log), income growth (2000-2010), share Black, racial segregation (Theil index), share population with a college degree, mean age, immigration, and the share working in manufacturing. The third model adds characteristics of the children in the Opportunity Insights data, namely the share married in their mid-30s, the fraction who stayed in the commuting zone they grew up in, and the proportion with a father present during early adolescence.

All covariates except for the children's outcomes (mobility, marriage, and stayed in the commuting zone) are measured in 2000, the year closest to when the children are claimed on their parent's income tax returns. For descriptive statistics of all variables in the main models, see Appendix Table A1. All variables are standardized to a mean of 0 and a standard deviation of 1 in all models. Appendix Figure A4 shows the correlation matrix of all variables in the main model specification.

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A. Appendix

Table A1: Descriptive statistics

	mean	sd	min	max
Upward mobility	0.43	0.06	0.23	0.67
Wealth inequality [Gini index]	0.77	0.03	0.70	0.86
Income inequality [Gini index]	0.41	0.08	0.25	0.85
Median household wealth [log]	11.60	0.34	10.73	12.98
Mean household income [log]	11.13	0.17	10.67	11.81
Population [log]	11.62	1.55	7.83	16.61
Income growth [2000-10]	-0.00	0.01	-0.12	0.04
Black [share]	0.07	0.11	0.00	0.61
Racial Segregation	0.13	0.10	0.00	0.55
College degree [share]	0.23	0.06	0.10	0.50
Age [mean]	51.18	1.88	43.93	57.67
Migration Inflow Rate	0.02	0.01	0.00	0.08
Share Working in Manufacturing	0.14	0.08	0.00	0.45
Married	0.41	0.10	0.10	0.77
Father present	0.68	0.09	0.44	0.94
CZ stayers	0.61	0.12	0.23	0.84
Observations		724		

Table A2: Full model results

	Model 1	Model 2	Model 3
Wealth inequality [Gini index]	-0.300***	-0.103*	-0.145***
	(0.03)	(0.05)	(0.02)
Income inequality [Gini index]		-0.199***	-0.061*
		(0.05)	(0.03)
Mean household wealth [log]		-0.392***	-0.328***
		(0.06)	(0.04)
Mean household income [log]		0.281***	0.391***
		(0.06)	(0.04)
Population [log]		-0.252***	0.035
		(0.05)	(0.06)
Income growth [2000-10]		0.255***	0.096*
		(0.03)	(0.04)
Black [share]		-0.277***	0.057*
		(0.03)	(0.02)
Racial Segregation		-0.069*	-0.004
		(0.03)	(0.02)
College degree [share]		0.420***	0.188***
		(0.07)	(0.04)
Age [mean]		0.316***	0.177***
		(0.05)	(0.02)
Migration Inflow Rate		-0.112***	-0.066***
		(0.03)	(0.02)
Share Working in Manufacturing		0.052	-0.065**
		(0.05)	(0.02)
Married			0.734***
			(0.05)
Father present			-0.015
			(0.04)
CZ stayers			-0.206***
			(0.05)
Constant	-0.000	-0.003	-0.001
	(0.03)	(0.02)	(0.01)
Observations	741	724	724

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Full model results (low-income college degree)

	Model 1	Model 2	Model 3
Wealth inequality [Gini index]	-0.159***	-0.161**	-0.215***
	(0.04)	(0.06)	(0.04)
Income inequality [Gini index]		-0.058	0.088+
		(0.06)	(0.05)
Mean household wealth [log]		-0.295***	-0.245**
		(0.08)	(0.08)
Mean household income [log]		-0.022	0.068
		(0.07)	(0.08)
Population [log]		-0.219**	0.312**
		(0.07)	(0.11)
Income growth [2000-10]		0.142+	0.026
		(0.07)	(0.08)
Black [share]		-0.000	0.176***
		(0.04)	(0.05)
Racial Segregation		-0.013	0.004
		(0.03)	(0.03)
College degree [share]		0.713***	0.443***
		(0.08)	(0.07)
Age [mean]		0.323***	0.180***
		(0.05)	(0.04)
Migration Inflow Rate		-0.114***	-0.115***
		(0.03)	(0.03)
Share Working in Manufacturing		0.001	-0.052
		(0.06)	(0.05)
Married			0.460***
			(0.07)
Father present			-0.013
			(0.07)
CZ stayers			-0.530***
			(0.08)
Constant	-0.000	-0.013	-0.014
	(0.03)	(0.03)	(0.03)
Observations	734	724	724

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Full model results (low-income marriage)

	Model 1	Model 2	Model 3
Wealth inequality [Gini index]	-0.367***	0.037	0.040
	(0.04)	(0.05)	(0.03)
Income inequality [Gini index]		-0.145*	-0.167***
		(0.06)	(0.04)
Mean household wealth [log]		-0.079	-0.106*
		(0.07)	(0.05)
Mean household income [log]		-0.142*	0.038
		(0.06)	(0.05)
Population [log]		-0.151**	0.242**
		(0.06)	(0.08)
Income growth [2000-10]		0.208***	0.131***
		(0.03)	(0.03)
Black [share]		-0.486***	-0.218***
		(0.03)	(0.03)
Racial Segregation		-0.106**	-0.064***
		(0.03)	(0.02)
College degree [share]		0.229***	0.172***
		(0.06)	(0.05)
Age [mean]		0.150***	0.145***
		(0.04)	(0.03)
Migration Inflow Rate		-0.085*	-0.052*
		(0.04)	(0.02)
Share Working in Manufacturing		0.173***	0.206***
		(0.04)	(0.03)
Father present			0.598***
			(0.05)
CZ stayers			-0.227**
			(0.08)
Constant	0.000	-0.003	0.005
	(0.04)	(0.02)	(0.02)
Observations	741	724	724

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Full model results (low-income marriage)

Table A6: Full model results (bottom 25th to top 25th)

	Model 1	Model 2
Wealth inequality [Gini index]	-0.325***	-0.158**
	(0.04)	(0.06)
Income inequality [Gini index]		-0.181***
		(0.03)
Mean household wealth [log]		-0.379***
		(0.09)
Mean household income [log]		0.409***
		(0.07)
Population [log]		-0.183***
		(0.06)
Income growth [2000-10]		0.299***
		(0.05)
Black [share]		-0.201***
		(0.03)
Racial Segregation		-0.159***
		(0.04)
College degree [share]		0.107*
		(0.05)
Age [mean]		0.138***
		(0.04)
Migration Inflow Rate		-0.159***
		(0.02)
Share Working in Manufacturing		-0.143***
		(0.04)
Constant	0.016	0.019
	(0.04)	(0.02)
Observations	712	704

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Full model results (causal place effect)

	Model 1	Model 2
Wealth inequality [Gini index]	-0.436***	-0.126**
	(0.03)	(0.04)
Income inequality [Gini index]		-0.268***
		(0.04)
Mean household wealth [log]		-0.350***
		(0.05)
Mean household income [log]		0.474***
		(0.06)
Population [log]		-0.203***
		(0.06)
Income growth [2000-10]		0.216***
		(0.03)
Black [share]		-0.303***
		(0.02)
Racial Segregation		-0.233***
		(0.04)
College degree [share]		0.034
		(0.04)
Age [mean]		0.135***
		(0.03)
Migration Inflow Rate		-0.138***
		(0.02)
Share Working in Manufacturing		-0.065*
		(0.03)
Constant	0.020	0.041
	(0.03)	(0.03)
Observations	702	697

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Full model results (White children)

	Model 1	Model 2	Model 3
Wealth inequality [Gini index]	-0.168***	-0.147**	-0.185***
	(0.04)	(0.05)	(0.04)
Income inequality [Gini index]		-0.162***	-0.065+
		(0.04)	(0.03)
Mean household wealth [log]		-0.477***	-0.318***
		(0.08)	(0.07)
Mean household income [log]		0.466***	0.431***
		(0.07)	(0.06)
Population [log]		-0.492***	0.115*
		(0.04)	(0.05)
Income growth [2000-10]		0.225***	0.142*
		(0.05)	(0.07)
Black [share]		-0.074*	0.008
		(0.03)	(0.03)
Racial Segregation		0.120***	0.034
		(0.02)	(0.02)
College degree [share]		0.350***	0.159***
		(0.06)	(0.05)
Age [mean]		0.267***	0.180***
		(0.04)	(0.03)
Migration Inflow Rate		-0.128***	-0.109***
		(0.03)	(0.02)
Share Working in Manufacturing		-0.119**	-0.103*
		(0.04)	(0.05)
Married [White]			0.535***
			(0.07)
Father present [White]			-0.025
			(0.08)
CZ stayers [White]			-0.381***
			(0.05)
Constant	0.000	0.006	0.001
	(0.04)	(0.03)	(0.02)
Observations	741	724	724

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A1: Wealth inequality exposure timing

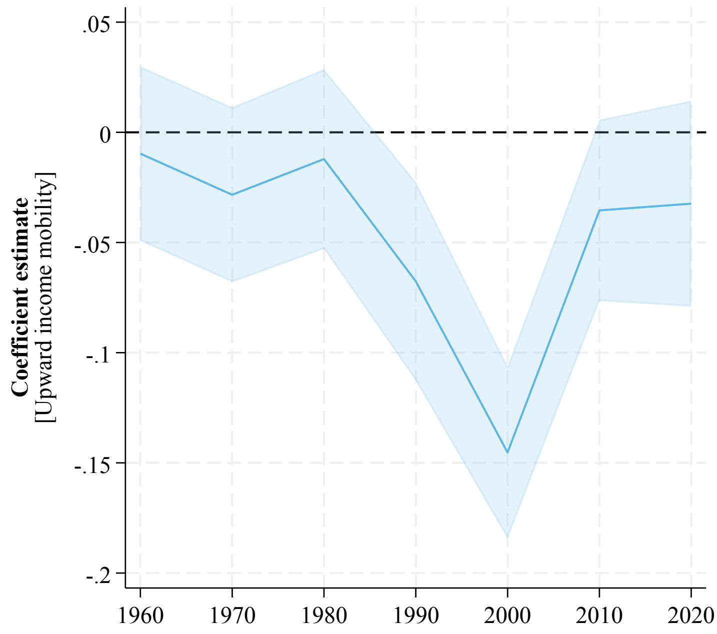

Figure A2: Distribution of wealth inequality (Gini index)

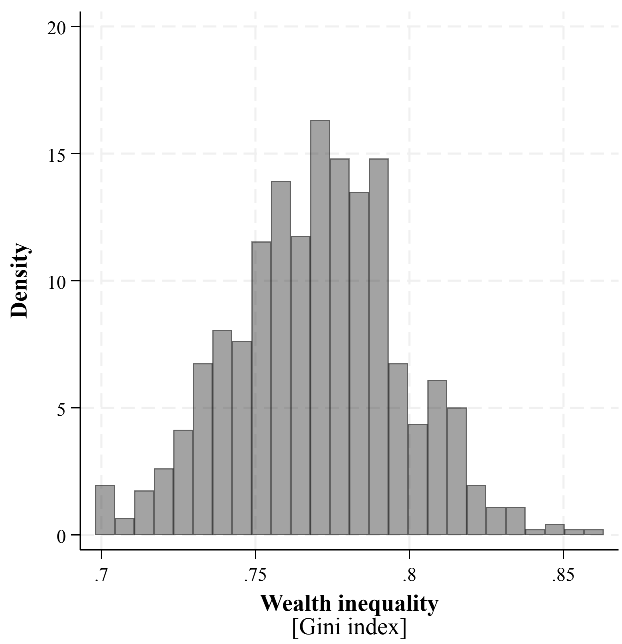

Table A9: Full model results (inverse variance weighting)

	Model 1	Model 2	Model 3
Wealth inequality [Gini index]	-0.176***	-0.123***	-0.097***
	(0.02)	(0.03)	(0.02)
Income inequality [Gini index]		0.024	-0.011
		(0.02)	(0.02)
Mean household wealth [log]		-0.206***	-0.181***
		(0.04)	(0.03)
Mean household income [log]		0.259***	0.298***
		(0.04)	(0.03)
Population [log]		-0.001	0.224***
		(0.03)	(0.03)
Income growth [2000-10]		0.329***	0.213***
		(0.03)	(0.02)
Black [share]		-0.331***	-0.066**
		(0.02)	(0.02)
Racial Segregation		-0.139***	-0.038*
		(0.02)	(0.02)
College degree [share]		0.119***	0.048*
		(0.03)	(0.02)
Age [mean]		0.127***	0.080***
		(0.02)	(0.02)
Migration Inflow Rate		-0.168***	-0.124***
		(0.01)	(0.01)
Share Working in Manufacturing		-0.074**	-0.108***
		(0.03)	(0.02)
Married			0.493***
			(0.04)
Father present			0.096**
			(0.03)
CZ stayers			-0.292***
			(0.03)
Constant	-0.318***	-0.177***	-0.031
	(0.03)	(0.03)	(0.02)
Observations	741	724	724

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: Full model results (winsorized)

	Model 1	Model 2	Model 3
Wealth inequality [Gini index]	-0.356***	-0.132***	-0.128***
	(0.03)	(0.04)	(0.03)
Income inequality [Gini index]		-0.194***	-0.087***
		(0.04)	(0.03)
Mean household wealth [log]		-0.359***	-0.261***
		(0.06)	(0.04)
Mean household income [log]		0.305***	0.393***
		(0.05)	(0.04)
Population [log]		-0.268***	0.044
		(0.05)	(0.05)
Income growth [2000-10]		0.239***	0.092***
		(0.04)	(0.03)
Black [share]		-0.281***	0.033
		(0.03)	(0.04)
Racial Segregation		-0.079**	-0.019
		(0.02)	(0.02)
College degree [share]		0.372***	0.146***
		(0.05)	(0.04)
Age [mean]		0.285***	0.155***
		(0.03)	(0.02)
Migration Inflow Rate		-0.124***	-0.083***
		(0.03)	(0.02)
Share Working in Manufacturing		0.004	-0.090***
		(0.03)	(0.02)
Married			0.631***
			(0.05)
Father present			0.052
			(0.04)
CZ stayers			-0.221***
			(0.04)
Constant	0.000	0.002	0.004
	(0.03)	(0.02)	(0.02)
Observations	741	724	724

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11: Full model results (individual-level)

	Model 1	Model 2	Model 3
Wealth inequality [Gini index]	-0.249***	-0.200***	-0.237***
	(0.04)	(0.04)	(0.04)
Income inequality [Gini index]		-0.198***	-0.097*
		(0.04)	(0.04)
Mean household wealth [log]		-0.518***	-0.484***
		(0.07)	(0.06)
Mean household income [log]		0.552***	0.641***
		(0.07)	(0.05)
Population [log]		-0.316***	0.097
		(0.06)	(0.08)
Income growth [2000-10]		0.215***	0.118*
		(0.05)	(0.06)
Black [share]		-0.109***	0.064
		(0.03)	(0.05)
Racial Segregation		-0.045	-0.024
		(0.03)	(0.03)
College degree [share]		0.424***	0.227***
		(0.05)	(0.04)
Age [mean]		0.331***	0.228***
		(0.05)	(0.03)
Migration Inflow Rate		-0.129***	-0.121***
		(0.02)	(0.03)
Share Working in Manufacturing		-0.051	-0.089*
		(0.04)	(0.04)
Married			0.351***
			(0.09)
Father present			0.069
			(0.06)
CZ stayers			-0.384***
			(0.07)
Constant	-0.000	-0.003	-0.002
	(0.03)	(0.02)	(0.03)
Observations	741	724	724

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: Full model results (bottom 99% Gini index)

	Model 1	Model 2	Model 3
Wealth inequality [Gini index]	-0.300***	-0.003	-0.120***
	(0.04)	(0.03)	(0.03)
Income Inequality [Gini index bottom 99%]		-0.438***	-0.110**
		(0.03)	(0.04)
Mean household wealth [log]		-0.293***	-0.295***
		(0.05)	(0.04)
Mean household income [log]		0.098	0.329***
		(0.06)	(0.04)
Population [log]		-0.113**	0.126**
		(0.04)	(0.04)
Income growth [2000-10]		0.309***	0.175***
		(0.03)	(0.03)
Black [share]		-0.144***	0.081**
		(0.03)	(0.03)
Racial Segregation		-0.050+	-0.011
		(0.03)	(0.02)
College degree [share]		0.317***	0.144***
		(0.04)	(0.03)
Age [mean]		0.264***	0.160***
		(0.03)	(0.02)
Migration Inflow Rate		-0.081***	-0.069***
		(0.02)	(0.02)
Share Working in Manufacturing		-0.036	-0.092***
		(0.03)	(0.02)
Married			0.724***
			(0.05)
Father present			-0.039
			(0.03)
CZ stayers			-0.236***
			(0.04)
Constant	-0.000	-0.032	-0.015
	(0.03)	(0.02)	(0.02)
Observations	741	707	707

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13: Full model results (regional)

	South	Non-South
Wealth inequality [Gini index]	-0.143***	-0.107***
	(0.03)	(0.03)
Income inequality [Gini index]	0.022	-0.122**
	(0.04)	(0.04)
Mean household wealth [log]	-0.416***	-0.268***
	(0.06)	(0.05)
Mean household income [log]	0.413***	0.422***
	(0.08)	(0.05)
Population [log]	-0.083	-0.018
	(0.07)	(0.07)
Income growth [2000-10]	0.128*	0.064
	(0.05)	(0.04)
Black [share]	-0.082*	-0.081
	(0.04)	(0.08)
Racial Segregation	-0.024	0.022
	(0.03)	(0.02)
College degree [share]	0.057	0.228***
	(0.05)	(0.04)
Age [mean]	0.148***	0.235***
	(0.03)	(0.03)
Migration Inflow Rate	-0.046	-0.026
	(0.03)	(0.02)
Share Working in Manufacturing	-0.137***	-0.035
	(0.03)	(0.03)
Married	0.335**	0.796***
	(0.12)	(0.05)
Father present	0.075	0.018
	(0.10)	(0.05)
CZ stayers	-0.102	-0.093
	(0.07)	(0.06)
Constant	-0.302***	-0.099*
	(0.06)	(0.04)
Observations	270	454

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A3: Distribution of upward income mobility

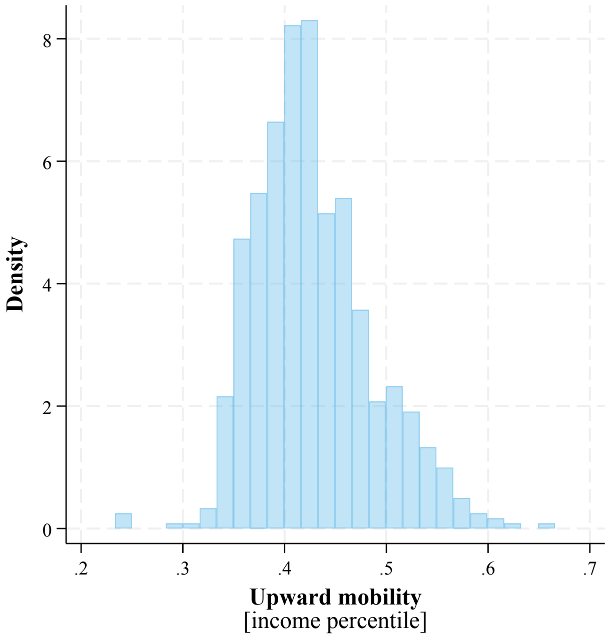

Figure A4: Correlation matrix